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Monitoring structural breaks in vegetation dynamics of the nature reserve Königsbrücker Heide

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ABSTRACT

Nowadays remote sensing is a well-established method and technique of providing data. The current development shows the availability of systems with very high geometric resolution for the monitoring of vegetation. At the same time, however, the value of temporally high-resolution data is underestimated, particularly in applications focusing on the detection of short-term changes. These can be natural processes like natural disasters as well as changes caused by anthropogenic interventions. These include economic activities such as forestry, agriculture or mining but also processes which are intended to convert previously used areas into natural or near-natural surfaces. The *Königsbrücker Heide* is a former military training site located about 30 km north of the Saxon state capitol Dresden. After the withdrawal of the Soviet forces in 1992 and after nearly 100 years of military use this site was declared as nature reserve in 1996. The management of the whole protection area is implemented in three different management zone. Based on MODIS-NDVI time series between 2000 and 2016 different developments are apparent in the nature development zone and the zone of controlled succession. Nevertheless, the analyses also show that short-term changes, so called breaks in the vegetation development cannot be described using linear trend models. The complete understanding of vegetation trends is only given if discontinuities in vegetation development are considered. Structural breaks in the NDVI time series can be found simultaneously in the whole study area. Hence it can be assumed that these breaks have a more natural character, caused for example by climatic conditions like temperature or precipitation. Otherwise, especially in the zone of controlled succession structural breaks can be detected which cannot be traced back to natural conditions. Final analyses of the spatial distribution of breakpoints as well as their frequency depending on the respective protection zone allow a detailed view to vegetation development in the Königsbrücker Heide.

Keywords: MODIS NDVI, time series analysis, regression analysis, protected areas, monitoring

1. INTRODUCTION

According to the Federal Agency for Nature Conservation (BfN), the object of research and monitoring is an integral part of resources management especially in the large protected areas of Germany (national parks, biosphere reserves, nature parks). The use of remote sensing methodology and data can make a valuable contribution to meet the special demands on monitoring of large areas. An additional advantage of using remote sensing for the monitoring of protected areas is the avoidance of the disturbance of ecosystems, since data collection is done without direct interaction.[1,2] An overview of the use of various remote sensing systems for different monitoring tasks for protected areas is given by Nagendra (2013).[3] Depending on the particular needs, a variety of remote sensing data are available with different temporal and spatial resolution but the selection is often limited by the availability of affordable data in order to minimize costs.[4]

Long-term montitoring can be done by time series analysis of repetitive collected data for at least ten years.[5] To evaluate the phenological status of vegetation high temporal resolution data are required. Therefore MODIS

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data are highly recommended because they provide a number of products for the description of phenology.[1] The Normalized Difference Vegetation Index (NDVI) is known as an important parameter for evaluating vegetation status over time.[6] Therefore NDVI times series of different remote sensing systems are available in different temporal and spatial resolutions (e.g. Terra MODIS NDVI, AVHRR GIMMS, SPOT VGT). They were used in numerous studies of vegetation monitoring in various vegetation zones and different scales ranging from global to local, showing the contribution using remote sensing data in conjunction with methods of applied spatial data analysis for monitoring programs in protected areas.[7–17] Especially high temporal resolution data allow a detailed analysis of short-term phenological processes. In the present study a former military training area is used to be examine discontinuities in vegetation development using temporal high-resolution satellite-based time series. These investigations are carried out for the *Königsbrücker Heide*, one of Germany's largest nature reserves.

2. MOTIVATION

As first analyses have proven, that MODIS NDVI time series are appropriate to investigate spatial and temporal changes in vegetation cover in the nature reserve *Königsbrücker Heide*.[18] The trend analyses performed using linear regression[19] and Mann-Kendall monotonic trend test[20–23] showed positive vegetation development in the entire study area. Different intensities of vegetation development can be recognized which are not clearly related to the different management zones. It was also stated that structural breaks in the time series can have a significant impact on the modeling and that a qualitatively better modeling can be expected, if the time of such structural break is considered as a discontinuity in the development and trend modeling before and behind this point is done separately.[18] For this reason the aim of the present study is to investigate the spatio-temporal distribution of structural breaks in the NDVI trend and their causes. The analyses carried out are based on the two following hypotheses:

1. Breakpoints occuring simultaneously in the whole study area are induced by climatic conditions.
2. Scattered breakpoints especially in the zone of controlled succession are caused by management measures.

In order to confirm the stated hypotheses several analyses are necessary. After the determination of the seasonality the MODIS NDVI time series is decomposed to extract the trend part. Then for the extracted trend a breakpoint detection is performed using BFAST.[24,25] As result of this detection the number of breaks in the observation period, the dates of these breaks and the magnitude of the breaks is available for each pixel. The methods used to confirm this hypotheses are introduced in chapter 4 before the results of the analyses are presented in chapter 5.

3. STUDY AREA AND DATA

In 1989 about 1.5 million soldiers were stationed in Germany. With the political changes in the early 1990s a substantial decline of the staff occurred. These processes entailed conversions of large areas not longer used for military purposes, especially in the new federal states in the eastern part of Germany. One of these conversion areas is the former military training area *Königsbrück*. This has already been created in 1906 by the Royal Saxon Army and is located about 30 km north of Saxony's capital Dresden. Until 1938 the Wehrmacht expanded the site by depopulating nine villages. After the end of WW2 the Soviet forces occupied the area and used it until their withdrawal in 1992. Since 1996 this territory is declared as the nature reserve (NSG) *Königsbrücker Heide*. The opportunity that one of the largest non-fragmented landscapes can develop mostly without human activities was enabled by the fact that large areas are restricted due to the still existing military equipment and weaponry remains. During more than 700 years history as a cultural landscape, the natural forest areas were reduced and used for forestry. In the period of military use large areas were kept free of forest. Since 1990, large areas reforest naturally in order to guarantee a free natural development in about 3/4 of the territory.

At present, the area has the status of a nature reserve and is, with an area of approximately $69.3\,\mathrm{km}^2$, one of the largest unfragmented nature reserves in Germany. The aim of the reserve is the assurance of large succession areas as retreat for species which have a high area requirement and are particularly sensitive to

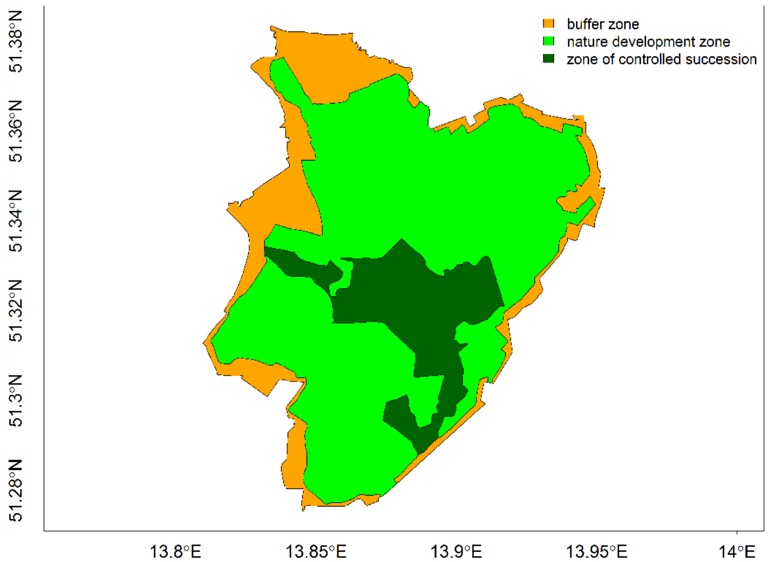

Figure 1. Protection zones of the Königsbrücker Heide

disturbances.[26] The *Königsbrücker Heide* is subdivided into three protection zones for achieving the protection aims (see figure 1). In the **nature development zone** with an area of about 50 km^2 no engagement, management and maintenance measures are carried out, except from ordnance disposal and maintenance of ways. By the development of the area without the impact of human activities the emergence of a natural forest environment under current condtitions is expected. As a result current habitats will gradually disappear. The **zone of controlled succession** (approximately 8 km^2) comprises former areas of military use, which are open land habitat for various species. In this zone succession processes are actively disturbed by selective intervention in order to preserve the open land habitat. The **buffer zone** serves as a buffer to the surrounding cultural landscape and occupies an area of about 10 km^2. Here existing pine forests are converted to natural forest and cultural habitats like fish ponds and meadows are preserved.[27]

For the investigation of relationship between vegetation and climate condition, rainfall data were included in the analysis. The data used for this study are freely available data of the DWD Climate Data Center. The grids of monthly total precipitation over Germany have a spatial resolution of 1 km and are based on DWD station data.[28,29] For the analysis of vegetation development in the study area, MODIS NDVI data were used, which are provided by the United States Geological Survey (USGS) since 2000 as worldwide NDVI time series in a spatial resolution of 250 m and with a repetition rate of 16 days which are capable to characterize vegetation change.[30,31] The investigation of the used data shows gaps that need to be removed before further processing in a time series analysis can take place. Therefore all data gaps in the study area are temporally interpolated using a seasonal Kalman filter.[32,33]

The second preprocessing step covers creating the subset of the study area by using the shape-files of the zones as well as an outline polygon of the area boundaries, which were provided by the administration of the protected area. Due to the geometric resolution of the data some pixels are intersected by the zone boundaries. By creating subsets of both data sets all pixels that are not covered by the polygon representing the study area were excluded.

At the end of preprocessing the data are temporally complete and categorized by zones available for the following time series analysis. Both data sets have a temporal coverage from February 2000 to January 2016 (15 years). Due to the repetition rate of 16 days 367 MODIS NDVI images are available for this observation period while the monthly rainfall data set comprises 192 images.

4. METHODOLOGY

The data analysis is organised in a multistage process. The preprocessing of the data, as described in the previous section, is followed by the decomposition of the time series and a breakpoint detection analysis. Furthermore the relationship of rainfall and NDVI was investigated by means of correlation analysis. The individual methods required to process this work flow are explained in the following section.

4.1 Methodology of decomposition

Each natural process which is periodical observed, for example by means of remote sensing time series data, can also be represented as a combination of a trend development, a periodical part of the signal and a random component. The process of separating the original signal into this three components is called decomposition. The output of this process are three (independent) components of the input signal:

- trend component (T)
- seasonal part (S)
- random residuals (e)

The relation between these components can have a more additive or multiplicative character, which depends on the stability of the seasonal parts' amplitude. The additive decomposition model is used if a stable seasonality is given, the multiplicative model otherwise.

$$Y = T + S + e \tag{1}$$

Basically this simple model of decomposition is performed for each MODIS-Pixel in the whole study area. The statistical language `R`[34] offers the function `decompose`. However this function needs the additional parameter of *frequency*. Because the used NDVI signal describes the annual recurring cycle of vegetation development it is assumed that this frequency of seasonality is given with 23 or 24 measurements. Still, this assumption has to be proven. Therefore different methods of analyzing seasonality (e.g. autocorrelation function, fast Fourier transformation)[35–37] are performed and finally these have confirmed the mentioned a priori assumption. Since the rainfall data are monthly data, the assumed frequency of seasonality is here 12 measurements, which was also confirmed by autocorrelation function.

To extract the trend component a moving average approach is chosen:

$$\underset{t_{max}+\frac{n}{2}}{\overset{t_{max}-\frac{n}{2}}{T_t}} = \frac{\sum_{i=t-\frac{n}{2}}^{i=t+\frac{n}{2}} Y_i}{n+1} \tag{2}$$

The length of the moving window corresponds to the frequency of seasonality of the original time series increased by 1. The seasonal figure itself can be computed after the trend component is removed (see equation 2). The seasonal figure arises by calculating the mean value of all NDVI measurements of a specific time in all periods. Finally the figure is centered. For one period (year), the seasonal part S_t can be expressed by:

$$\underset{i=1}{\overset{n}{S_i}} = \frac{\sum_{j=0}^{m-1} Y_{j\cdot n+i}}{m} \tag{3}$$

Where m corresponds to the number of years. Removing the trend component as well as the seasonal figure from the original signal, the error component remains.

$$e_t = Y_t - (T_t + S_t) \tag{4}$$

The workflow is performed for all pixels in the study area and the quality of that process is proven by means of different methods of residual analyses using the random part of decomposition.

4.2 Methodology of breakpoint detection

The determination of breakpoints using the BFAST-approach (Breaks for additive seasonal and trend) combines the decomposition of a time series into seasonal, trend, and remainder as already explained in chapter 4.1 with the detection of breaks respectively changes within the series. This approach also allows the determination of structural breaks within the seasonal as well as the trend component. Because that the decomposition was already performed at this point of the workflow, the BFAST-approach is applied only on the trend component. Therefore the seasonal component is set to 0 and the input series (original trend component of the NDVI time series) is separated in trend and remainder. BFAST itself looks for significant changes in the input series using the ordinary least-squares residual-based moving sum (OLS-MOSUM).[38] Furthermore a robust regression calculation is performed for each segment between the detected breakpoints. The segment-specific slopes and intercepts of these segments are the results of a M-estimation.[36] More detailed information about the mentioned methods are available in Verbesselt et al. (2010),[24,39] Bai and Perron (2003),[40] and Zeileis et al. (2002).[25]

BFAST is part of the R-package strucchange.[41] The regression lines are characterised most of all by the position of the breakpoints. Which in turn are strongly influenced by the parameter h. This parameter defines the minimal segment size between two potential breakpoints as the minimal fraction of the length of the whole input time series.[24,39] Based on the findings of Osunmadewa et al. (2015)[42] several tests are performed on the sensitivity of the results of break point detection regarding a chosen h-value. The results indicate, that the h-value of 0.15 and 0.20 best reflects the course of the trend signal. Besides the visual interpretation of the results, two other criteria can help to asses the quality of breakpoint detection. The first one is the spread of the confidence interval of the breakpoints. This shows an increase of the spread when the h-value is reduced. The second criterion used the quality of the linear regression of the segments. Therefore the standard deviation of the residuals are calculated and compared for the results of different h-values. This shows an increasing of the standard deviation with increasing h-value. Finally it can be stated, that the h-value of 0.15 and 0.20 are well chosen and corresponds to a minimum segment size of 2 years and three months or 3 years respectively.

4.3 Methodology of cross correlation

The existence of serial correlations is a major factor which complicates statistical inference of time series analysis.[35] The autocorrelation of a single time series can be computed using the auto correlation function estimation (ACF).[36,37] Here the signal is compared to itself at different time shifts and the time shift (lag) with the maximum correlation ist determined. In contrast the cross correlation (CCF) calculates the correlation of two different signals at different time shifts.[36] In this study the autocorrelation function was used to prove the assumption that the natural rhythm of vegetation cover has a frequency of one year. This information of frequency is a parameter passed to the decomposition process and has great impact on the decomposition quality. But of even more importance in this present study is the calculation of cross correlation between vegetation development represented by the NDVI time series and climate conditions represented by the rainfall time series.

5. RESULTS

5.1 Results of decomposition of time series

The decomposition of the time series was carried out according to the explanations in chapter 4.1 using the additive approach. The decomposition comprise 1207 time series for the NDVI data set and 88 time series for the rainfall. The quality of the decomposition was confirmed by a detailed residual analysis using KPSS test, ADF test and PP test.[43,44] As always proven by previous studies, for the processed KPSS test, the maximum test values for level stationary (0.028) and trend stationary (0.014) for the NDVI for the whole study are below the corresponding critical values ($L_{crit} = 0.463$; $T_{crit} = 0.146$). Thus, the null hypothesis of stationarity is proven for each single time series.[44] These findings were confirmed by the ADF test and the PP test and therefore it can be assumed that the decomposition of the time series was successful. Finally the trend component is available for further analysis.

5.2 Results of breakpoint detection

As explained in chapter 4.2 the breakpoint detection was perfomed by using the BFAST package.[39] Since the choice of parameter h has great impact on the resulting segmentation by defining the minimal segment size between two breakpoints, for the NDVI time series as well as for rainfall time series the breakpoint detection was performed with two different h values ($h = 0.2$ and $h = 0.15$) for comparison. Then a scatterplot between time of break and magnitude of break was used to identify intervals of simultaneous breakpoints by visual interpretation. The definition of these intervals was based on shifts in mean of magnitude and temporal gaps between break times. Based on these findings the results of the different breakpoint detections were rearranged according to the identified periods. This way, the following information are available for further analysis and interpretation for each performed breakpoint calculation:

- the number of breakpoints for each pixel
- the spatial distribution of break dates of each breakpoint interval
- the spatial distribution of magnitudes of each breakpoint interval

With the help of these maps it is possible to separate breakpoint intervals with breakpoint appearance in the whole study area from intervals with scattered break points. Furthermore it is possible to link the spatial distribution of breaks in NDVI with the management zones. Finally the comparison of the results of NDVI and rainfall can be used to verify the first hypothesis (see chapter 2).

5.2.1 Breakpoint detection for NDVI

At first the breakpoint detection for the NDVI time series was performed with BFAST with parameter $h = 0.2$. In this case the maximum number of breaks is limited to five breaks. In fact, for the used data set the maximum number of detected breaks per pixel ranges between two and three in the study area. For further investigation of spatio-temporal distribution of these breaks a scatterplot between time of break and magnitude of break was used to identify and specify periods with simultaneous occurrence of breakpoints. With the scatterplot shown in figure 2, seven break intervals were defined by visual analysis explained in chapter 5.2. The corresponding limits of these intervals are given in table 1.

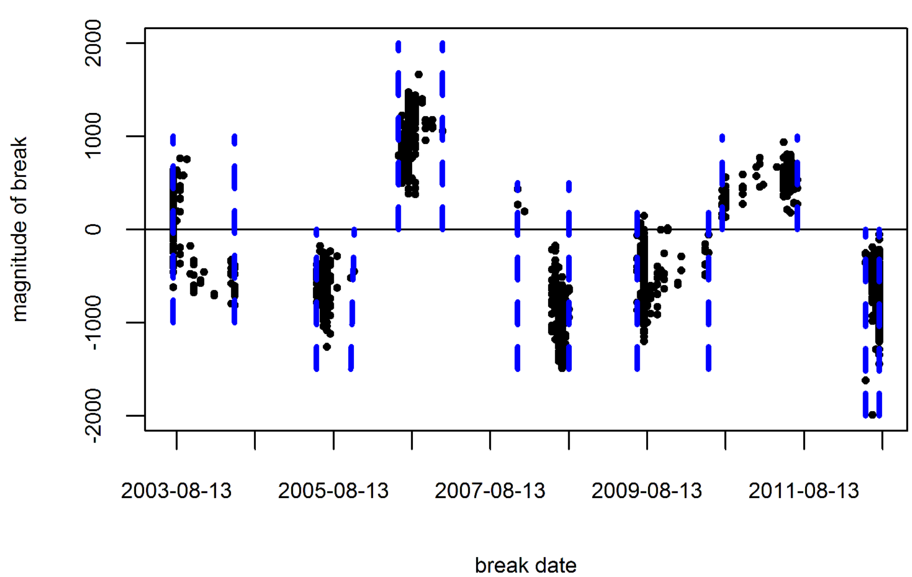

Figure 2. Scatterplot for break times and magnitudes for NDVI with $h = 0.2$; defined break point intervals (blue dashed lines)

Table 1. Breakpoint intervals for the NDVI data set using BFAST with h = 0.2

Interval	**Lower Limit**	**Upper Limit**	**width [no. of obs.]**
1	07/2003	05/2004	18
2	05/2005	11/2005	11
3	06/2006	01/2007	13
4	12/2007	08/2008	15
5	06/2009	05/2010	21
6	07/2010	07/2011	22
7	05/2012	07/2012	4

The findings of this visual cluster analysis was used to create maps of the distribution of break dates (see figure 3, top) and distribution of magnitudes (see figure 3, bottom) for each breakpoint interval. As can be seen in the scatterplot (see figure 2 and figure 3, bottom) positive as well as negative magnitudes can be found in the observation period. Especially in the first interval both kinds of magnitudes can be found at different places in the study area. Furthermore, breakpoint intervals exist with breakpoint occurrence in nearly the whole study area (interval 3, 5 and 7), while there are also intervals with only a few scattered breakpoints in the study area. Also the absolute value of magnitudes varies between the break intervals. For quality assessment the breakpoint detection was plotted for selected pixels in order to verify a proper segmentation of the NDVI trend by visual inspection. In most cases the detected breaks are in line with the visual interpretation, but it has to be mentioned, that also breaks exists in single pixels, which seem not to fit the visual impression. Possible causes for these mismatches will be discussed later in the final chapter 6.

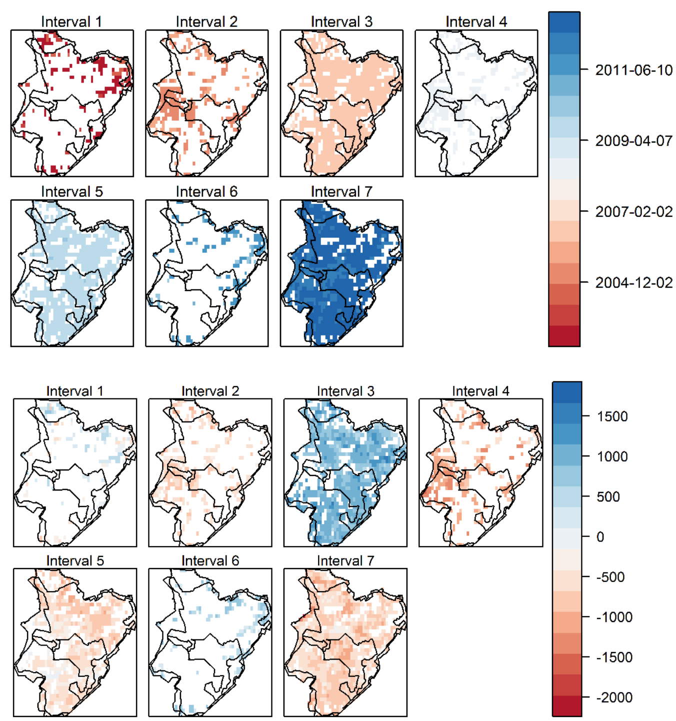

Figure 3. Top: Distribution of break dates for each breakpoint interval for NDVI with h = 0.2; Bottom: Distribution of magnitudes for each breakpoint interval for NDVI with h = 0.2

For comparison, the break point detection for the NDVI trend part was performed additionally with h = 0.15 and the same processing steps were applied for determining the breakpoint intervals. The h value of 0.15 allows a maximum number of 6 breakspoints in the observation period. For the study area the number of breaks per pixel ranges between 3 and 5 breakpoints. By visual interpretation of the associated scatterplot (see figure 4) 9 intervals were classified. The ranges of these 9 intervals are given in table 2.

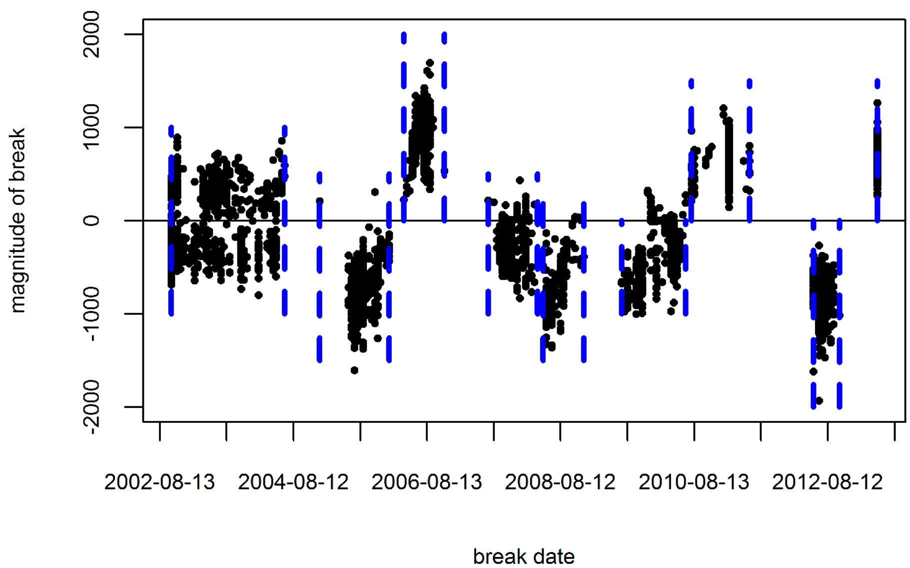

Figure 4. Scatterplot for break times and magnitudes for NDVI with h = 0.15; defined break point intervals (blue dashed lines)

Table 2. Breakpoint intervals for the NDVI data set using BFAST with h = 0.15

Interval	Lower Limit	Upper Limit	width [no. of obs.]
1	10/2002	06/2004	51
2	01/2005	01/2006	24
3	04/2006	11/2006	14
4	07/2007	04/2008	17
5	05/2008	12/2008	14
6	07/2009	06/2010	22
7	07/2010	05/2011	20
8	05/2012	10/2012	9
9	05/2013	05/2013	0

Similar to the first approach, both directions of magnitude can be found in the observation period. And here also in the first interval the spread of magnitudes is very high. Again, since it is not possible to check all 1207 performed breakpoint detection individually, some selected pixel were used for quality assessment. By visual impression it can be stated, that the detected breaks using h = 0.15 match slightly better than for h = 0.2.

The maps for the identified intervals for the distribution of break dates (see figure 5, top) and distribution of magnitudes (see figure 5, bottom) show that also with this parameter setting, intervals with simultaneous breaks in the whole study area can be found (interval 1, 3, 6 and 8), as well as periods with less breakpoint occurrences.

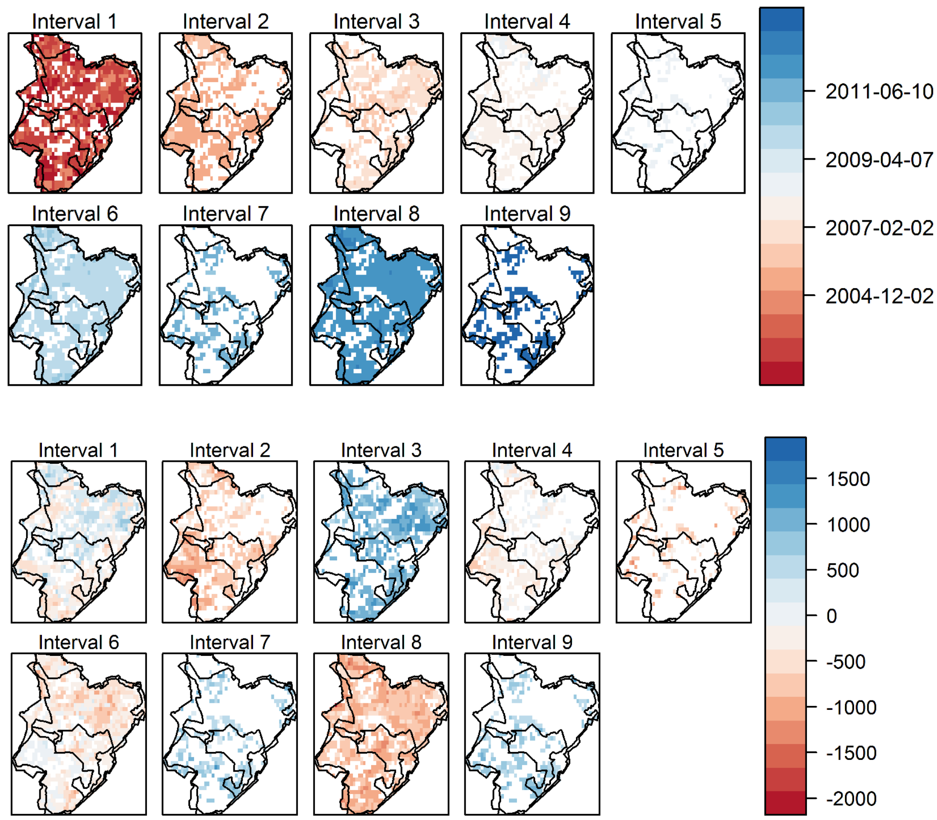

Figure 5. Top: Distribution of break dates for each breakpoint interval for NDVI with h = 0.15; Bottom: Distribution of magnitudes for each breakpoint interval for NDVI with h = 0.15

When compared to the results for h = 0.2, it can be seen, that the temporal range, the spatial distribution as well as the magnitudes differ between both approaches, but there also exist temporal and spatial overlap.

5.2.2 Breakpoint detection for rainfall

The rainfall data were used to confirm the first hypothesis. The same processing steps like for the NDVI time series were applied to the rainfall time series. After the preprocessing (cf. chapter 3) decomposition was performed for each time series in order to extract the trend part. Then the breakpoint detection was performed using BFAST with h = 0.2 and some selected pixels were chosen for quality assessment. The visual inspection of the BFAST plots for these selected location revealed, that h = 0.2 does not lead to meaningful results. For this reason no further analysis was applied for this approach. In contrast, the breakpoint detection with h = 0.15 is mainly in line with the visual break point detection. Therefore only these results are part of the further analysis of the rainfall development and will be the basis for the investigation of the relationship between rainfall conditions and vegetation development.

Running BFAST with h = 0.15 for the study area leads to 4 or 5 breaks per pixels. With the help of the scatterplot (shown in figure 6) 6 breakpoint intervals were classified for the rainfall data. The ranges of these 6 intervals are given in table 3.

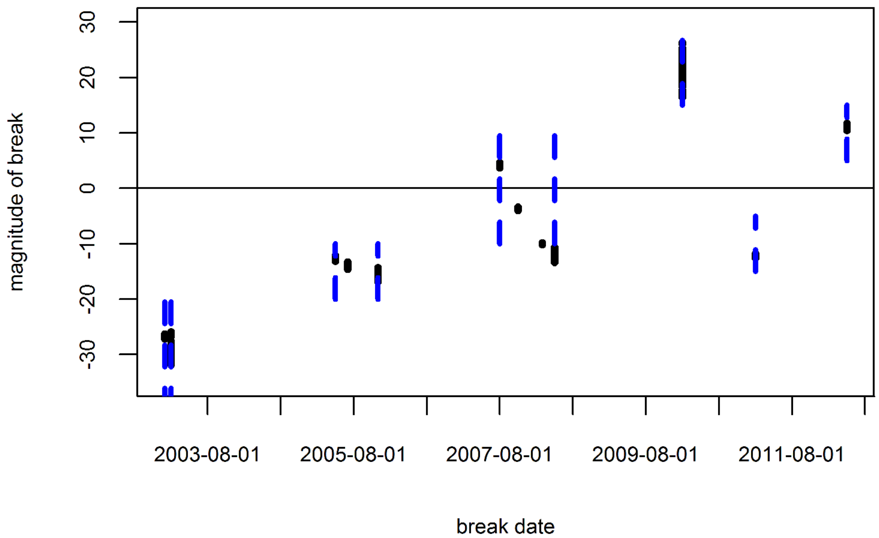

Figure 6. Scatterplot for break times and magnitudes for rainfall with h = 0.15; defined break point intervals (blue dashed lines)

Table 3. Breakpoint intervals for the rainfall data set using BFAST with h = 0.15

Interval	**Lower Limit**	**Upper Limit**	**width [no. of obs.]**
1	01/2003	02/2003	1
2	05/2005	12/2005	7
3	08/2007	05//2008	9
4	02/2010	02/2010	0
5	02/2011	02/2011	0
6	05/2012	05/2012	0

The maps based on the identified intervals for the distribution of break dates (see figure 7, top) and distribution of magnitudes (see figure 7, bottom) show that the first three break intervals cover the whole study area, while the latter ones show only break points in parts of the study area.

5.3 Results of correlation analysis for NDVI and rainfall

In order to examine the relationship between the area-wide break intervals for NDVI and area-wide break intervals for rainfall, the results of both data sets were compared. For the NDVI both segmentations, with h = 0.2 (three out of seven intervals have area wide-break point occurrence) and h = 0.15 (four out of nine intervals have area wide break point occurrence) were used for that investigation. But since h = 0.2 did not provide plausible results for rainfall, only the results for h = 0.15 were included in the comparison with NDVI break points.

For all three data sets was investigated, whether there is a temporal relationship between the simultaneous breaks in the rainfall and the area-wide breaks in the NDVI as well as a relationship for the direction of the breaks of both signals (e.g. decline in rainfall induces decline in vegetation development). When the intervals of the NDVI breaks and their corresponding magnitudes are compared to that of the rainfall analysis, there seems to be more plausible relationship between the NDVI for h = 0.15 than for h = 0.2. There are (apparently) temporal correlations between area-wide breakpoint intervals of both measurements (also with respect to the magnitude direction).

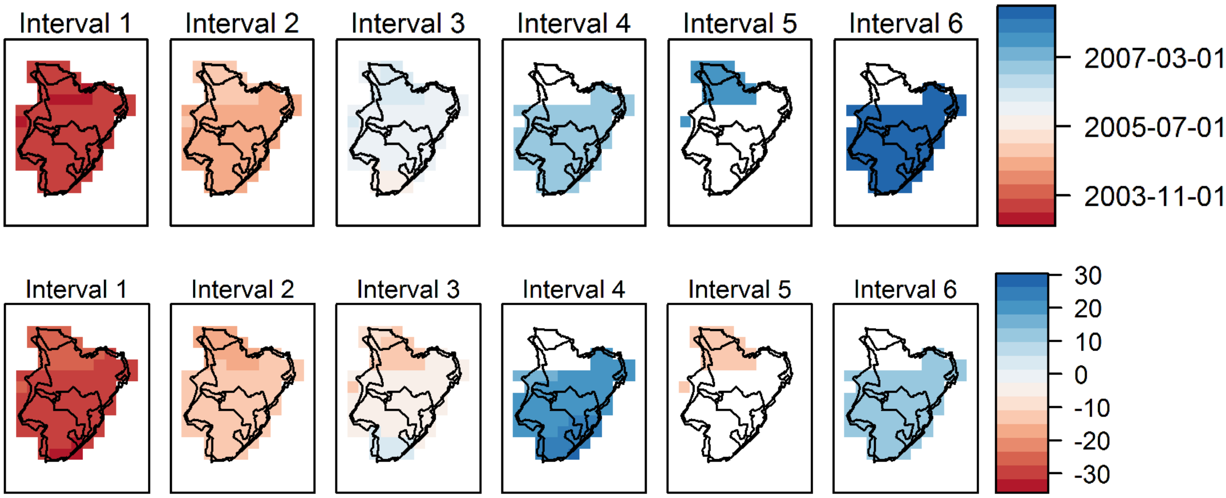

Figure 7. Top: Distribution of break dates for each breakpoint interval of rainfall for $h = 0.15$; Bottom: Distribution of magnitudes for each breakpoint interval of rainfall for $h = 0.15$

First the areal rainfall break takes place and then a break of the same direction can be observed in the NDVI with some time delay. But since not all simultaneous break intervals can be traced back to abrupt changes in rainfall, the question arises how large the temporal distance between rainfall-break and NDVI break can be, in order to determine a dependence between both events.

Therefore, a cross-correlation was carried out for both measured values. The correlation was carried out for the original data (including the seasonality) and the trend parts. The analysis for the original data serves to establish a general connection between rainfall and vegetation growth. On the other hand, analysing the correlation of both trends can show, whether there is also a dependency on long-term development in addition to the (likely) seasonal relation.

In order to be able to perform the cross-correlation, the data sets had to be homogenised, first since both data sets have different spatial and temporal resolutions. Therefore, the NDVI data (original and trend) were aggregated to monthly values by calculating the monthly mean. And the rainfall data were resampled to the spatial resolution of the NDVI data set using nearest neighbor interpolation. Subsequently, the calculation of the cross-correlation, introduced in chapter 4.3, for each pixel was done for both original and trend data.

The result is a two-layer image. The first layer contains the maximum correlation for both time series of that pixel (How strong is the relationship?). The second layer provides the information, for which lag (shift of the signals) this maximum correlation exists. The results of the cross-correation analysis for the orignal data is shown in figure 8. For the orignal series, with a maximum of 0.33, the correlation between rainfall and NDVI is not very high, but significant for almost the entire study area. The maps show, that the higher correlations mainly occur in the areas of dense vegetation or for tree population. In areas, where rather the heath vegetation dominates (in the zone of controlled succession), lower correlations occur.

On the other hand, for the trend parts of both time series, only less relationships can be verified (see figure 9). For the lags (shift in time), three peaks can be observed for lag = 1 month, lag = 6 month and lag = 12 month. With about 50 % a lag of 12 month occurs most frequently. However, a link between current growth and the rainfall a year ago may be questioned. It is possible, that the correlations at these points are similar for a further time (shorter lag), but there are currently no findings and further investigations are needed. In approximately 40 % of the cases, the maximum correlation was about 6 months and this temporal distance is quite conceivable.

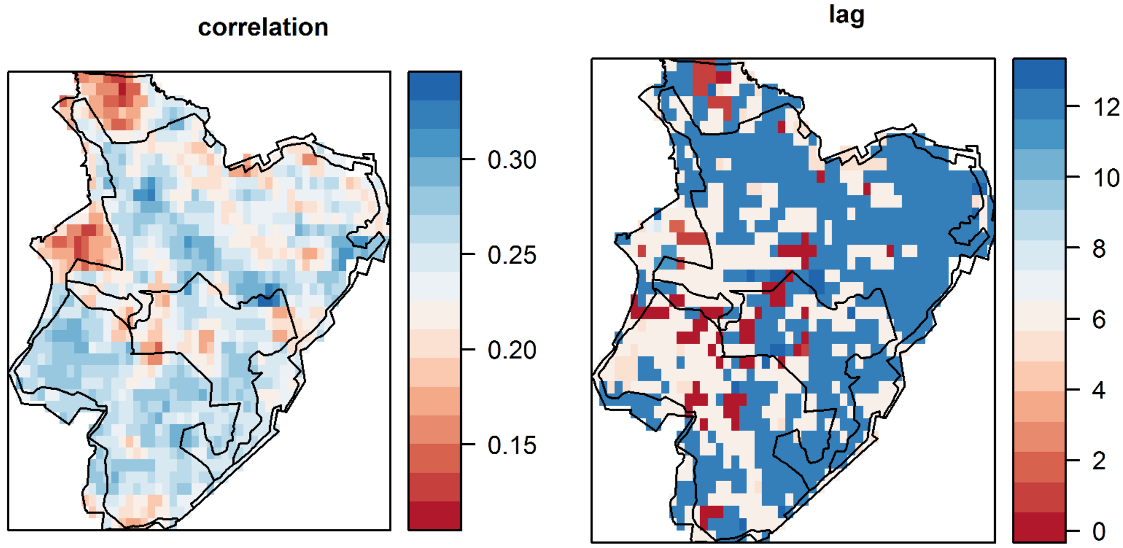

Figure 8. Cross-correlation between original rainfall and original NDVI; left: maximum correlation; right: lag (in months) for maximum correlation

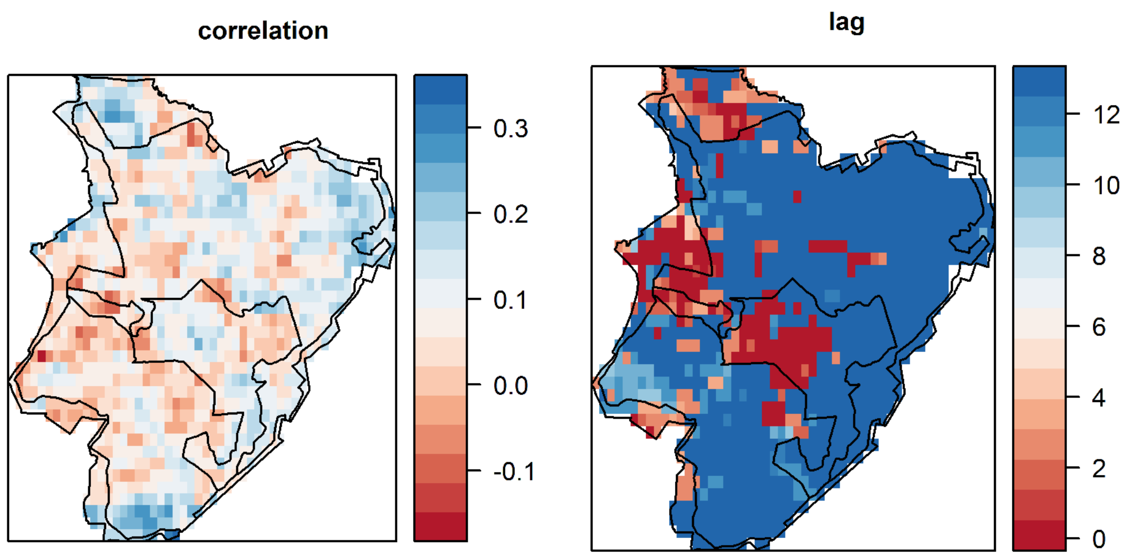

Figure 9. Cross-correlation between trend part of rainfall and trend part of NDVI; left: maximum correlation; right: lag (in months) for maximum correlation

5.4 Comparison of breakpoint occurrence and nature reserve management

To verify the second hypothesis, two sample pixels were selected from the zone of controlled succession. The information about measures implemented in that zone were provided by the administration of the protected area. In the area of the selected sample time series the measurements took place in 2010. Now the question arises, whether these measurements (in this case the removal of trees) can be recognised by the breakpoint detection. Since the results for h = 0.15 reveal slightly better results, these segmentation was used to investigate coincidence of breaks and management activities. The results of breakpoint detection of the two samples are shown in figure 10. It can be easily seen, that both trend parts shown a sudden decrease in 2010. But when both breakpoint

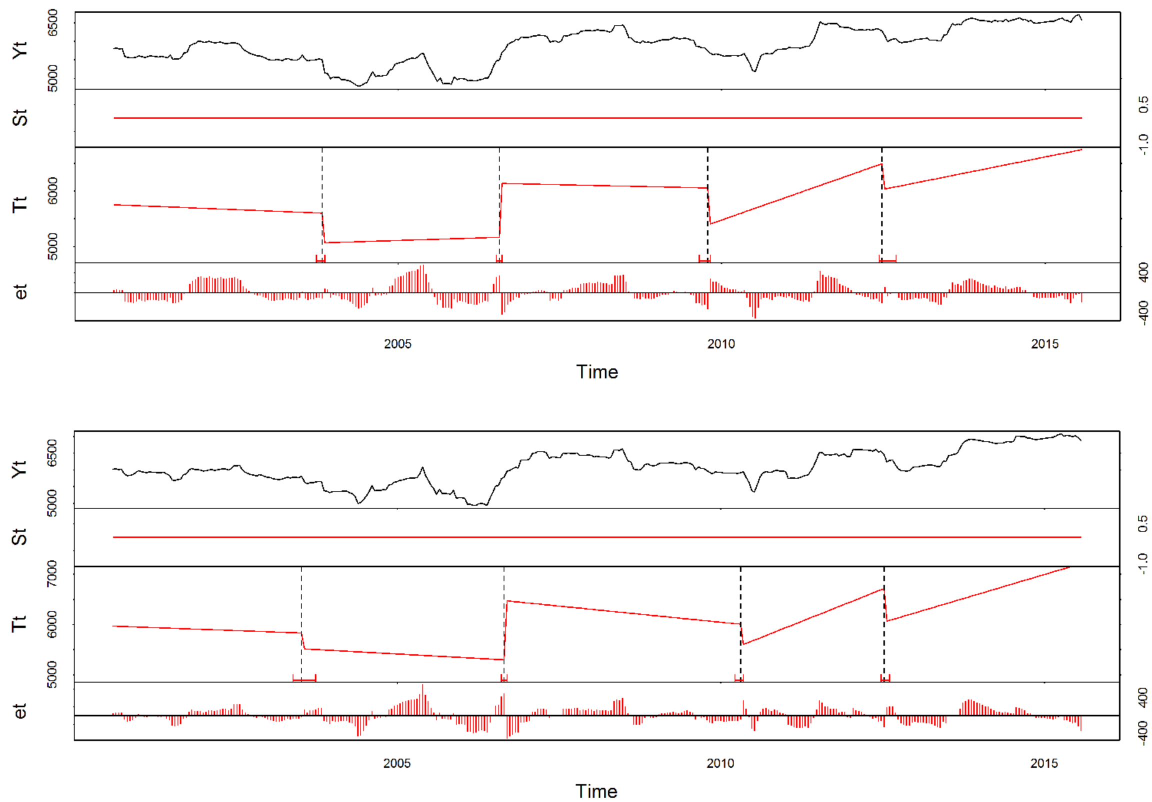

Figure 10. Breakpoint detection in the zone of controlled succession; top: sample point 1; bottom: sample point 2

detection are compared to each other it has to be stated that both results show a breakpoint. But the break date differs and the break in 2010 detected in the second sample (see figure 10, bottom) has more correspondence to the visible decrease in the NDVI trend. Unfortunately only the year but not the exact time of the measurement is known. Therefore, it is rather difficult to associate the sudden decrease with the measurement. For this reason, at this point of investigation the second hypothesis can neither be proved nor refuted.

6. DISCUSSION & SUMMARY

The two hypotheses, introduced at the beginning of chapter 2, are intended as the basis for the following critical analysis of data and methods used in this present study. One limitation is given by the spatial resolution of 250 m of the NDVI data set. Since the biodiversity in the study area is high, vegetation development can be assumed as highly variable at small scale and therefore, it is questionable to what extent these different developments can be recorded by the MODIS NDVI data. As already mentioned in the previous chapter, information on the exact date and extent of management activities in the zone of controlled succession are not sufficient and this limits the investigation of the second hypothesis. Since information about management activities are only available since 2009, no earlier breakpoints could be investigated for agreement.

Regarding the analysis in order to prove the first hypothesis both data sets, the NDVI as well as the rainfall, have to be critically reviewed. The rainfall data are gridded data with a spatial resolution of 1 km, interpolated based on DWD station data, which is quite coarse in relation to the NDVI time series. For this reason it has to be scrutinised, to which extent spatial differences in rainfall distribution can be recorded by the data.

The second issue which needs to be addressed, are the methods used in the analysis process. For the removal of the seasonal part of both time series the simple decomposition was used. This method assumes constant seasonality (amplitudes) in the whole observation period. However, because conversion processes take place in the study area, it could be more appropriate to allow changes in seasonality in the decomposition of the NDVI time series. Furthermore the trend part is extracted by a moving average approach. Since the moving average works as low-pass filter, high frequent parts in the signal can be attenuated, which can cause the removal of breaks in short periods.

As already mentioned and partly explained in the methodology chapter for the breakpoint detection (cf. chapter 4.2) the parameter h, which defines the minimum segment size between two consecutive breakpoints, has great impact on the result of the segmented linear regression. By this means, the maximum number of breaks within the analysed observation period is fixed without considering the real circumstances. If two anomalies occur in shorter temporal distance than defined by the minimum segment size, not both will be detected. If a breakpoint detection has to be performed for a whole study area instead of single series, methods for quality assessment are needed to investigate the proper segmentation for a larger area. One hint can be provided by the range of the confidence intervals for each detected break. These information are illustrated in figure 11 for the NDVI using h = 0.15. Especially for the first break interval rather broad confidence intervals occur. In combination with the spread of break dates in that interval (cf. figure 4) is it likely, that not all breaks in this interval are detected correctly. Therefore higher flexibility and sensitivity for the detection of changes is needed.

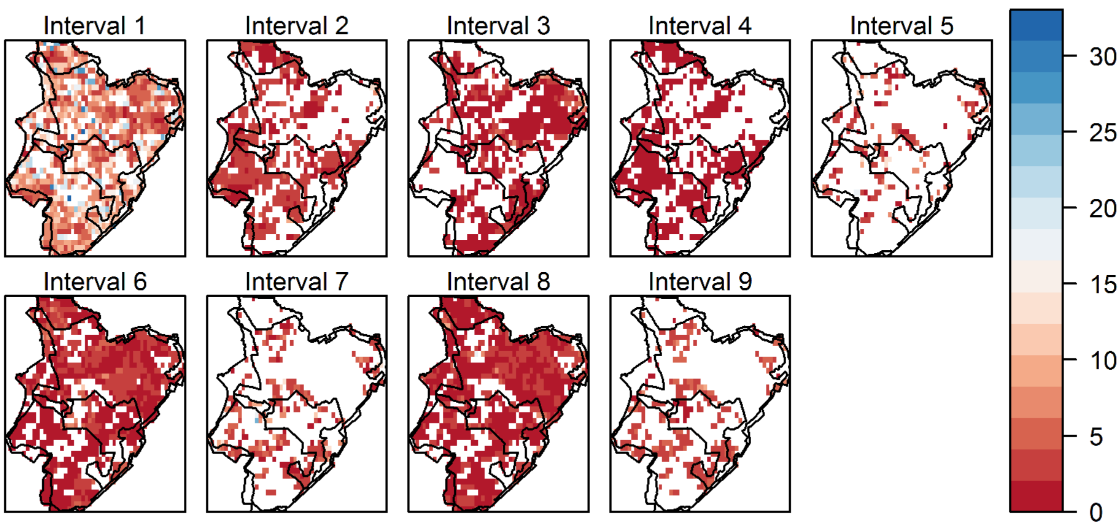

Figure 11. Spread of confidence intervals for each breakpoint in each interval for NDVI (h = 0.15)

Finally also the correlation analysis needs to be discussed. Here the different spatial and temporal resolution of the NDVI data (250 m, bi-monthly) and rainfall data (1 km, monthly) limit the statistical significance of the correlation analysis. In the presented approach only the lag (shift in time) for the maximum correlation was recorded. For the correlation analysis of both trend parts, about 50 % of the time series show the maximum correlation for a lag of 12 month. Further investigations are needed to identify possible reasons. This can indicate options for the improvement of the correlation analysis. At the same time the actual approach should be expanded to record other combinations of high correlation (apart from the maximum correlation) and their corresponding lag.

For both hypothesis formulated at the beginning, no clear statement can be made whether to confirm or refute them. But it is hardly impossible to relate the management activities to changes in the NDVI development because of coarse information about the activities and the weak relation between the spatial resolution of the NDVI data and the intensity of management activities. For the selected sample points it is known, that this area is dominated by heath and in order to maintain the typical vegetation composition and an open landscape, only the trees were removed by the management activities. Here the question arises, whether this removal of scattered trees can be detected as a change in NDVI with a spatial resolution of 250 m. Here satellite images with higher spatial resolution can provide better information. The maximum correlation between NDVI and rainfall revealed in the correlation analysis was about 30 %. This implies, that the consideration of only rainfall can not fully explain the simultaneous occurrence of NDVI breaks in the whole study area. Consequently it is necessary to include other climate parameter. Additionally it could be useful to investigate the influence of soil conditions in the study area on vegetation development.

REFERENCES

[1] Willis, K. S., "Remote sensing change detection for ecological monitoring in united states protected areas," *Biological Conservation* **182**, 233 – 242 (2015).

[2] Pettorelli, N., Laurance, W. F., O'Brien, T. G., Wegmann, M., Nagendra, H., and Turner, W., "Satellite remote sensing for applied ecologists: opportunities and challenges," *Journal of Applied Ecology* **51**(4), 839–848 (2014).

[3] Nagendra, H., Lucas, R., Honrado, J. P., Jongman, R. H., Tarantino, C., Adamo, M., and Mairota, P., "Remote sensing for conservation monitoring: Assessing protected areas, habitat extent, habitat condition, species diversity, and threats," *Ecological Indicators* **33**, 45 – 59 (2013). Biodiversity Monitoring.

[4] Nemani, R. R., Ganguly, S., Dungan, J., Gao, F., Melton, F. S., Milesi, C., Wang, W., Votava, P., Michaelis, A., and Myneni, R., "Mapping vegetation leaf area index globally at 30m using landsat/global land survey data," *AGU Fall Meeting Abstracts* (2009).

[5] Lindenmayer, D. B. and Likens, G. E., "The science and application of ecological monitoring," *Biological Conservation* **143**(6), 1317 – 1328 (2010).

[6] Rouse, Jr., J. W., Haas, R. H., Schell, J. A., and Deering, D. W., "Monitoring Vegetation Systems in the Great Plains with Erts," *NASA Special Publication* **351**, 309 (1974).

[7] Wessels, K., van den Bergh, F., and Scholes, R., "Limits to detectability of land degradation by trend analysis of vegetation index data," *Remote Sensing of Environment* **125**, 10 – 22 (2012).

[8] Lambert, J., Jacquin, A., Denux, J. P., and Chéret, V., "Comparison of two remote sensing time series analysis methods for monitoring forest decline," in [*Analysis of Multi-temporal Remote Sensing Images (Multi-Temp), 2011 6th International Workshop on the*], 93–96 (July 2011).

[9] Karlsen, S. R., Tolvanen, A., Kubin, E., Poikolainen, J., Hogda, K. A., Johansen, B., Danks, F. S., Aspholm, P., Wielgolaski, F. E., and Makarova, O., "Modis-ndvi-based mapping of the length of the growing season in northern fennoscandia," *International Journal of Applied Earth Observation and Geoinformation* **10**(3), 253 – 266 (2008).

[10] Jacquin, A., Sheeren, D., and Lacombe, J.-P., "Vegetation cover degradation assessment in madagascar savanna based on trend analysis of modis ndvi time series," *International Journal of Applied Earth Observation and Geoinformation* **12, Supplement 1**, S3 – S10 (2010). Supplement Issue on "Remote Sensing for Africa - A Special Collection from the African Association for Remote Sensing of the Environment (AARSE)".

[11] Hutchinson, J., Jacquin, A., Hutchinson, S., and Verbesselt, J., "Monitoring vegetation change and dynamics on u.s. army training lands using satellite image time series analysis," *Journal of Environmental Management* **150**, 355 – 366 (2015).

[12] Fensholt, R., Rasmussen, K., Nielsen, T. T., and Mbow, C., "Evaluation of earth observation based long term vegetation trends - intercomparing ndvi time series trend analysis consistency of sahel from AVHRR GIMMS, Terra MODIS and SPOT VGT data," *Remote Sensing of Environment* **113**(9), 1886 – 1898 (2009).

[13] de Jong, R., de Bruin, S., de Wit, A., Schaepman, M. E., and Dent, D. L., "Analysis of monotonic greening and browning trends from global ndvi time-series," *Remote Sensing of Environment* **115**(2), 692 – 702 (2011).

[14] de Beurs, K. M. and Henebry, G. M., "A statistical framework for the analysis of long image time series," *International Journal of Remote Sensing* **26**(8), 1551–1573 (2005).

[15] Awange, J., Ferreira, V., Forootan, E., Khandu, Andam-Akorful, S., Agutu, N., and He, X., "Uncertainties in remotely sensed precipitation data over africa," *International Journal of Climatology* (2015).

[16] Weiss, E., Marsh, S. E., and Pfirman, E. S., "Application of noaa-avhrr ndvi time-series data to assess changes in saudi arabia's rangelands," *International Journal of Remote Sensing* **22**(6), 1005–1027 (2001).

[17] Pinzon, J. E. and Tucker, C. J., "A non-stationary 1981-2012 avhrr ndvi3g time series," *Remote Sensing* **6**(8), 6929–6960 (2014).

[18] Wessollek, C. and Karrasch, P., "Monitoring of vegetation dynamics on the former military training area königsbrücker heide using remote sensing time series," *Proc. SPIE* **10005**, 100050Q–100050Q–12 (2016).

[19] Hutcheson, G. D., "Ordinary least-squares regression," in [*The SAGE dictionary of quantitative management research*], Moutinho, L. and Hutcheson, G. D., eds., 224–228, SAGE Publications Ltd (2011).

[20] Gilbert, R. O., [*Statistical methods for environmental pollution monitoring*], Van Nostrand Reinhold, Van Nostrand Reinhold (1987).

[21] Hipel, K. W. and McLeod, A. I., [*Time series modelling of water resources and environmental systems*], vol. 45, Elsevier (1994).

[22] Tabari, H. and Hosseinzadeh Talaee, P., "Recent trends of mean maximum and minimum air temperatures in the western half of iran," *Meteorology and Atmospheric Physics* **111**(3-4), 121–131 (2011).

[23] Ramesh, A., [*Response of Flood Events to Land Use and Climate Change, Analyzed by Hydrological and Statistical Modeling in Barcelonnette, France*], Springer Theses, Springer Netherlands (2013).

[24] Verbesselt, J., Hyndman, R., Zeileis, A., and Culvenor, D., "Phenological change detection while accounting for abrupt and gradual trends in satellite image time series," *Remote Sensing of Environment* **114**(12), 2970 – 2980 (2010).

[25] Zeileis, A., Leisch, F., Hornik, K., and Kleiber, C., "strucchange: An r package for testing for structural change in linear regression models," *Journal of Statistical Software* **7**, 1–38 (1 2002).

[26] Klenke, F., ed., [*Naturschutzgebiete in Sachsen*], Sächsisches Staatsministerium für Umwelt und Landwirtschaft (2008).

[27] Reppel, A. L., "Besucherkonzept für die königsbrücker heide - endbericht," tech. rep., Universität Paderborn (2003).

[28] DWD Climate Data Center (CDC), "Grids of monthly total precipitation over germany, version v1.0.," (2017).

[29] Kaspar, F., Müller-Westermeier, G., Penda, E., Mächel, H., Zimmermann, K., Kaiser-Weiss, A., and Deutschländer, T., "Monitoring of climate change in germany - data, products and services of germany's national climate data centre," *Advances in Science and Research* **10**(1), 99–106 (2013).

[30] Zhang, X., Friedl, M. A., Schaaf, C. B., Strahler, A. H., Hodges, J. C., Gao, F., Reed, B. C., and Huete, A., "Monitoring vegetation phenology using modis," *Remote Sensing of Environment* **84**(3), 471 – 475 (2003).

[31] Huete, A., Didan, K., Miura, T., Rodriguez, E., Gao, X., and Ferreira, L., "Overview of the radiometric and biophysical performance of the modis vegetation indices," *Remote Sensing of Environment* **83**(1-2), 195 – 213 (2002). The Moderate Resolution Imaging Spectroradiometer (MODIS): a new generation of Land Surface Monitoring.

[32] Kalman, R. E., "A new approach to linear filtering and prediction problems," *Journal of basic Engineering* **82**(1), 35–45 (1960).

[33] Eiurridge, P. and Wallis, K. F., "Seasonal adjustment and kalman filtering: Extension to periodic variances," *Journal of Forecasting* **9**(2), 109–118 (1990).

[34] Kendall, M. and Stuart, A., [*The Advanced Theory of Statistics*], vol. 3, Griffin (1983).

[35] Hong, Y., "Serial correlation and serial dependence." wise working paper series WISEWP0601 (June 2006).

[36] Venables, W. N. and Ripley, B. D., [*Modern Applied Statistics with S*], Springer, New York, fourth ed. (2002). ISBN 0-387-95457-0.

[37] Box, G. E. P., Jenkins, G. M., and Reinsel, G. C., [*Time series analysis / forecasting and control*], John Wiley & Sons; Hoboken, New Jersey, Wiley, 4. ed. (2008).

[38] Zeileis, A., "A unified approach to structural change tests based on ml scores, f statistics, and ols residuals," *Econometric Reviews* **24**(4), 445–466 (2005).

[39] Verbesselt, J., Hyndman, R., Newnham, G., and Culvenor, D., "Detecting trend and seasonal changes in satellite image time series," *Remote Sensing of Environment* **114**(1), 106 – 115 (2010).

[40] Bai, J. and Perron, P., "Computation and analysis of multiple structural change models," *Journal of Applied Econometrics* **18**(1), 1–22 (2003).

[41] Zeileis, A., Leisch, F., Hornik, K., Kleiber, C., and Hansen, B., *Package 'strucchange'* (2015).

[42] Osunmadewa, B. A., Wessollek, C., and Karrasch, P., "Linear and segmented linear trend detection for vegetation cover using gimms normalized difference vegetation index data in semiarid regions of nigeria," *Journal of Applied Remote Sensing* **9**(1), 096029 (2015).

[43] Phillips, P. C. B. and Perron, P., "Testing for a unit root in time series regression," *Biometrika* **75**(2), 335–346 (1988).

[44] Kwiatkowski, D., Phillips, P. C., Schmidt, P., and Shin, Y., "Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root?," *Journal of Econometrics* **54**(1-3), 159–178 (1992).